A Bayesian Model of Multimodal Visuo-motor Adaptation

A Bayesian Model of Multi-modal Visuomotor Adaptation

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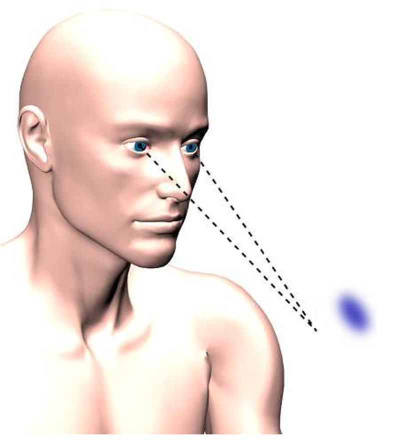
Summary

- We propose a model of multi-modal adaptation of reaching movements based on optimal Bayesian inference of the causes of errors
- Our model accounts for the patterns of trial-to-trial adaptation as well as perceptual aftereffects in vision and proprioception when visual feedback is shifted or rotated.

Motivation

Perceptual aftereffects of adaptation to shifted visual feedback

Many studies have reported that adaptation to shifted visual feedback induces shifts in both visual and proprioceptive perception [7, 2, 5].



Visual perceptual shift

- Subjects asked to locate a visual or proprioceptive (right fingertip) target with their unseen left fingertip
- Persistent shift in perceived location of both visual and proprioceptive targets after exposure to shifted visual feedback
- Visual shift aftereffect < Imposed shift
  $\Longrightarrow$ Some component of adaptation at the motor level

Proprioceptive perceptual shift

Existing Models

Maximum Likelihood-Based sensor recalibration [1, 7]

- Discrepancy between vision and proprioception eliminated by adjusting each estimate towards max. likelihood estimate (MLE)
  - Does not use knowledge of issued motor commands
  - No component of motor adaptation
- Can plausibly be combined with a distinct motor adaptation model to fully describe trial-to-trial behaviour
  - Independent sensor calibration and motor adaptation
  - Tacitly assumed in [7] to infer relative precision of vision and proprioception
- No direct experimental evidence to support independent sensor/motor adaptation

Modelling Framework

Model of a generic visuomotor adaptation experiment

Simplified model of a single reaching trial under experimentally controlled perturbations:

- Final hand position y_t depends on motor command u_t, motor disturbance r_t^u and motor noise ϵ_t^u

$$y_t = u_t + r_t^u + \epsilon_t^u; \qquad \epsilon_t^u \sim N(0, \sigma_u^2)$$

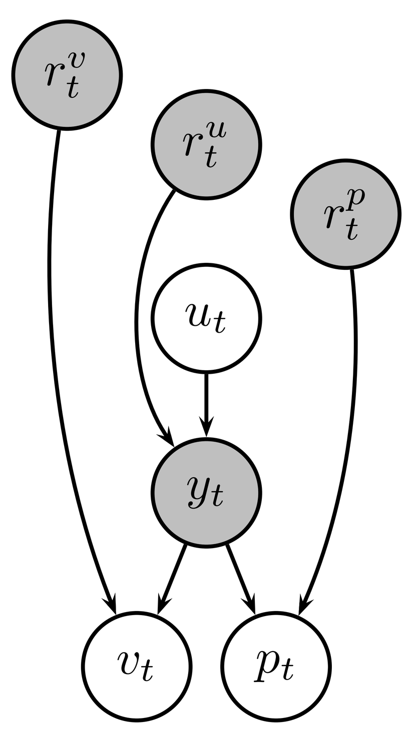
  - r_t^u controlled via manipulandum, inertial load
- Subjects' visual observation of hand position is noisy and shifted

$$v_t = y_t + r_t^v + \epsilon_t^v; \qquad \epsilon_t^v \sim N(0, \sigma_v^2)$$

  - r_t^v controlled via prisms, virtual reality apparatus
- Proprioceptive observation is also noisy and perturbed

$$p_t = y_t + r_t^p + \epsilon_t^v; \qquad \epsilon_t^p \sim N(0, \sigma_p^2)$$

  - r_t^p manipulated by vibration of muscles (less common)



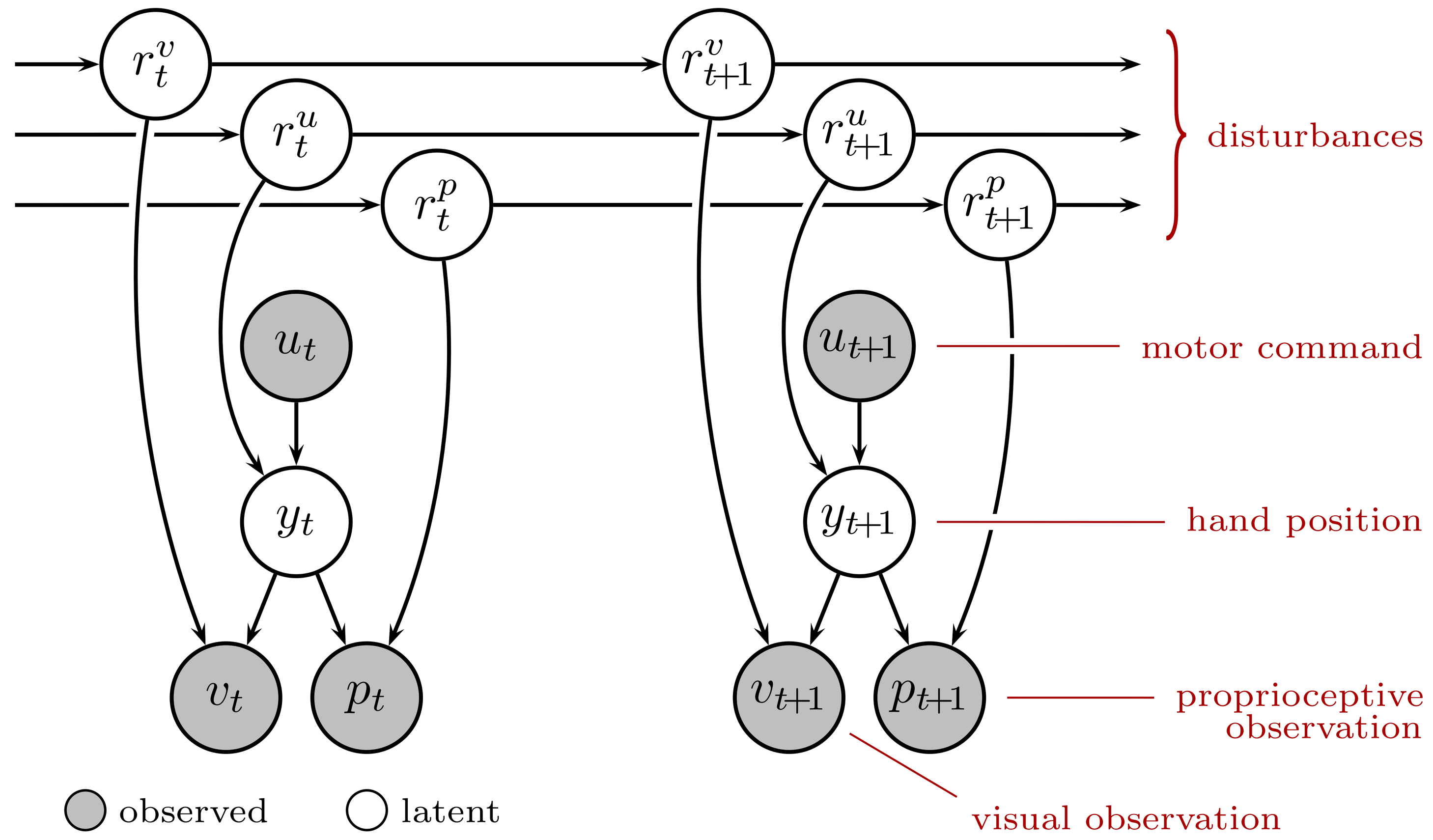
- Equivalent assumptions are quite common in the motor adaptation literature, e.g. [7] (Vision/Proprioception model), [6] (Dynamics model)

Bayesian Adaptation Model

A unified approach to motor adaptation and sensor recalibration

Optimal joint inference of the three potential sources of systematic error.

- What the subject believes and observes:



- Subject maintains a statistical estimate of the total disturbance $\mathbf{r}_t = (r_t^v, r_t^p, r_t^u)^T$
- Subject has internal model of how disturbances are liable to vary over time [3, 4]

$$\mathbf{r}_{t+1} = A\mathbf{r}_t + \boldsymbol{\xi}_t\ ; \qquad \boldsymbol{\xi}_t \sim N(0, Q) \tag{1}$$

- Current beliefs about disturbance represented as a mulivariate Gaussian:

$$P(\mathbf{r}_t) \propto e^{-\frac{1}{2}(\mathbf{r}_t - \hat{\mathbf{r}}_{t|t})^T P_{t|t}^{-1}(\mathbf{r}_t - \hat{\mathbf{r}}_{t|t})}$$

  - $\hat{\mathbf{r}}_{t|t}$ = Estimate after trial t
  - $P_{t|t}$ = Uncertainty
- Motor commands chosen on each trial according to most likely set of disturbances

Optimal inference of the disturbances

Subject infers posterior estimate of the disturbances given new observations from each trial, motor commands issued, and prior beliefs (posterior from previous trial)

- Equivalent to a Kalman filter with latent state $\mathbf{r}_t$, state transition model (1) and observation model:

$$\begin{pmatrix} v_t - u_t \\ p_t - u_t \end{pmatrix} = \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \end{pmatrix} \begin{pmatrix} r_t^v + \epsilon_t^v \\ r_t^p + \epsilon_t^p \\ r_t^u + \epsilon_t^u \end{pmatrix} \qquad \text{or} \qquad \mathbf{z}_t = H(\mathbf{r}_t + \boldsymbol{\epsilon}_t)$$

- Observation noise: $\quad H\boldsymbol{\epsilon}_t \sim N(0, R); \qquad R = \begin{pmatrix} \sigma_v^2 + \sigma_u^2 & \sigma_u^2 \\ \sigma_u^2 & \sigma_p^2 + \sigma_u^2 \end{pmatrix}$
- Standard Kalman filter updates yield optimal estimate $\hat{\mathbf{r}}_{t|t-1}$, $P_{t|t-1}$ at the start of each new trial. This dictates choice of motor command u_t on each trial and therefore the hand position y_t predicted by the model.

MLE-based Model Details

Although no explicit model has previously been proposed, existing models of motor adaptation and sensor recalibration can be plausibly combined.

- Max. Likelihood estimation of hand position (MLE) from vision and proprioception

$$\hat{y}_t = \frac{\sigma_p^2}{\sigma_v^2 + \sigma_p^2}(v_t - \hat{r}_t^v) + \frac{\sigma_v^2}{\sigma_v^2 + \sigma_p^2}(p_t - \hat{r}_t^p)$$

- Uni-modal motor adaptation using hand position MLE

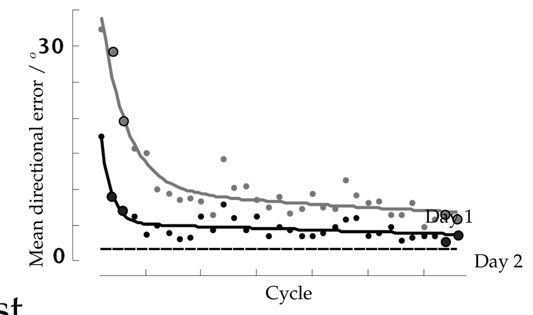
$$\hat{r}_{t+1}^u = \hat{r}_t^u + \beta(u_t + \hat{r}_t^u - \hat{y}_t)$$

- Sensor recalibration eliminates sensory discrepancy by adjusting each estimate towards MLE [1]

$$\begin{aligned} \hat{r}_{t+1}^v &= \hat{r}_t^v + \gamma\sigma_p^2[(v_t - \hat{r}_t^v) - (p_t - \hat{r}_t^p)] \\ \hat{r}_{t+1}^p &= \hat{r}_t^p + \gamma\sigma_v^2[(p_t - \hat{r}_t^p) - (v_t - \hat{r}_t^v)] \end{aligned}$$

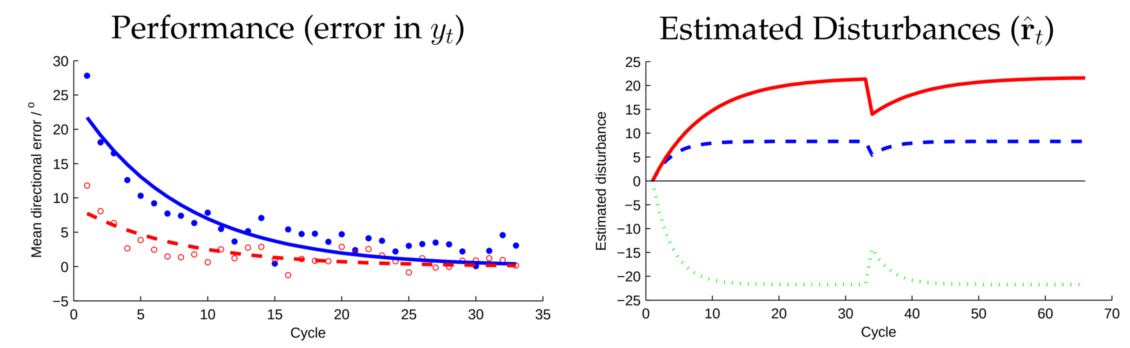
Results

- Both models fitted to data using Matlab (`lsqnonlin`)
- Data taken from [4]:
  - Reaching to 8 targets around a circle
  - Data represents average over cycle of 8 targets
  - Day 1 - Adaptation to 30^o rotation of visual feedback
  - Day 2 - Retesting on same 30^o rotation
- Overnight forgetting model: $\hat{\mathbf{r}}_T = B\hat{\mathbf{r}}_{T-1}$ (T = first trial of new day)
- Free parameters:
  - Bayesian: $\sigma_v^2,\ \sigma_p^2,\ \sigma_u^2,\quad A = \begin{pmatrix} a & \cdot & \cdot \\ \cdot & a & \cdot \\ \cdot & \cdot & a \end{pmatrix},\quad B = \begin{pmatrix} b & \cdot & \cdot \\ \cdot & b & \cdot \\ \cdot & \cdot & b \end{pmatrix},\quad Q = \begin{pmatrix} q_v & \cdot & \cdot \\ \cdot & q_p & \cdot \\ \cdot & \cdot & q_u \end{pmatrix}$
  - MLE-based: $\sigma_v^2,\ \sigma_p^2,\ \sigma_u^2,\ \beta,\ \gamma,\ b$



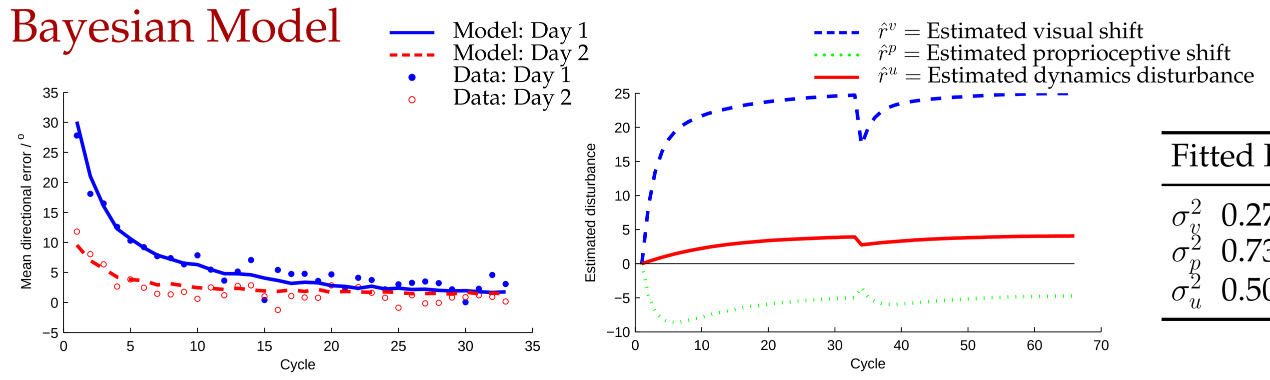
Original data

MLE-based Model



Fitted Parameters			
σ_v^2	0.0845	q_v	0.0219
σ_p^2	0.0189	q_p	0.0144
σ_u^2	1.6380	q_u	0.0050
		a	0.9961
		b	0.7000

Bayesian Model



Fitted Parameters			
σ_v^2	0.2789	β	0.1187
σ_p^2	0.7320	γ	0.0052
σ_u^2	0.5050	b	0.6534

Conclusions

- Unified approach to motor adaptation and sensor recalibration
- Able to account for perceptual aftereffects of adaptation to shifted visual feedback
- Multiple modelled disturbances leads to richer adaptation dynamics
  - Good agreement with experimental data
  - Bayesian model provides superior fit compared to MLE-based model

Future Work

- Experimental testing of model predictions
  - Can changes in dynamics elicit perceptual aftereffects in the same way that shifted visual feedback can?
- Improved parameter estimation (EM-based)
- Extension to nonlinear disturbances/adaptation
  - Different generalization patterns for kinematic vs dynamic disturbances

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